Active Multistatic Track Initiation Cued by Passive Acoustic Detection

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***Abstract*—Fields of distributed passive and multistatic active sonar sensors provide surveillance capabilities against quiet submarine threats in Anti-Submarine Warfare scenarios. The joint cooperative use of passive and active sonar offers synergistic and complimentary acoustic performance as well as operational advantages. However, a significant challenge of heterogeneous, multi-sensor systems is the successful fusion of information from the various sensors to enable robust target detection, classification, localization, and tracking.**

This paper describes a fusion algorithm which is based on a passive acoustic detection cue that triggers a multistatic active sonar system. It provides the capability to reduce false track rate by selectively initiating active tracks via a passive cue. The algorithm is developed for the case of fixed passive arrays, which are unable to determine target range. However, the passive system may automatically detect Closest-Point-of-Approach (CPA) events and forward these as cues to the active system for multistatic active track initiation. The passive range and bearing ambiguities, time-of-CPA and speed-to-range ratio as provided by CPA detections are then mapped into a set of hypotheses in a 4-dimensional Cartesian space (x and y positions and velocities) via a Gaussian Mixture representation for active track initiation. The highly probable target state hypothesis is identified within a multi-bank multistatic tracker. The paper describes the algorithm and presents results on a simulated passive-active dataset. It demonstrates the effective "hand off" of the cue, target localization, tracking and false alarm reduction.

Keywords–Data fusion; Sonar Equation; Multistatic; Passive; Sonar; Cue; Gaussian Mixture

I. Introduction

Distributed sonar networks have the potential to increase Anti-Submarine Warfare (ASW) performance against small, quiet, threat submarines in the harsh clutter-saturated littoral and deeper ocean environments. This improved performance comes through the expanded geometric diversity of distributed fields and the complementary capabilities of passive and multistatic active sonar sensors [1]. The cumulative effect of all sensors, when their information is effectively fused, provides increased area coverage, probability of detection, classification, localization, tracking, and false alarm reduction. The effectiveness of cueing approaches to mitigate false track rate has been shown for active multistatic systems [2], where a loud active (specular) echo provides an effective cue. This paper describes a different cue that is from a cooperating passive acoustic sensor. The resulting algorithm is referred to as the "pQa" or "passive cueing active" algorithm.

A heterogeneous mix of both passive acoustic and active multistatic sonar sensors offers complimentary acoustic and operational performance benefits. Passive sensors are covert and provide the tactical advantage that targets are unaware of their detection vulnerability. Active sonars are overt systems and targets may react to their operations. Passive sonar typically has much shorter detection ranges and smaller area coverage than active sonar, due to the quiet nature of modern submarine threats. With loud source pings, active sonar can achieve greater signal excess and detection ranges, and may be suitable for target tracking over larger areas. Therefore, a passive detection may serve as an effective initial detection and cue to trigger active sonar operations, and initiate multistatic target tracking with a focused search area provided by the passive detection. Active multistatic sonar will eventually track targets over a larger open area. False alarms are prevalent for both sensing types; a passive system may be confused by nearby and distant shipping, while an active system may be flooded with reverberation clutter. An effective passive cueing active algorithm will help mitigate the false alarm rate.

A disadvantage of a single, fixed, passive sensor array is the difficulty in determining a precise geographic localization of detected targets. In addition to the range ambiguities, fixed horizontal line arrays have an azimuthal ambiguity around the axis of the array. However, for constant velocity targets, monitoring bearing measurements over time enables the detection of Closest-Point-of-Approach (CPA) events [3]. Besides the target's time of CPA, CPA detections provide estimates of the target's heading and speed-to-range ratio. If Doppler shift measurements are also available, it becomes possible to obtain a target's velocity estimate. Therefore the target's range-at-CPA can be calculated from the speed-to-range ratio. In this paper, we assume that sufficiently accurate Doppler shift measurements are not available for obtaining accurate velocity or range estimates. We map the CPA parameters which are time of CPA, target's heading and speed-to-range ratio into a set of target localization and velocity hypotheses, via a Gaussian Mixture (GM) representation in the Cartesian coordinate frame. These hypotheses are then fused with active measurements. For example, at the time of CPA, the target may be located at any range on the CPA bearing line. Its heading

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14. ABSTRACT

Fields of distributed passive and multistatic active sonar sensors provide surveillance capabilities against quiet submarine threats in Anti-Submarine Warfare scenarios. The joint cooperative use of passive and active sonar offers synergistic and complimentary acoustic performance as well as operational advantages. However, a significant challenge of heterogeneous multi-sensor systems is the successful fusion of information from the various sensors to enable robust target detection classification, localization, and tracking. This paper describes a fusion algorithm which is based on a passive acoustic detection cue that triggers a multistatic active sonar system. It provides the capability to reduce false track rate by selectively initiating active tracks via a passive cue. The algorithm is developed for the case of fixed passive arrays, which are unable to determine target range. However the passive system may automatically detect Closest-Point-of- Approach (CPA) events and forward these as cues to the active system for multistatic active track initiation. The passive range and bearing ambiguities, time-of-CPA and speed-to-range ratio as provided by CPA detections are then mapped into a set of hypotheses in a 4-dimensional Cartesian space (x and y positions and velocities) via a Gaussian Mixture representation for active track initiation. The highly probable target state hypothesis is identified within a multi-bank multistatic tracker. The paper describes the algorithm and presents results on a simulated passive-active dataset. It demonstrates the effective ???hand off??? of the cue, target localization, tracking and false alarm reduction.

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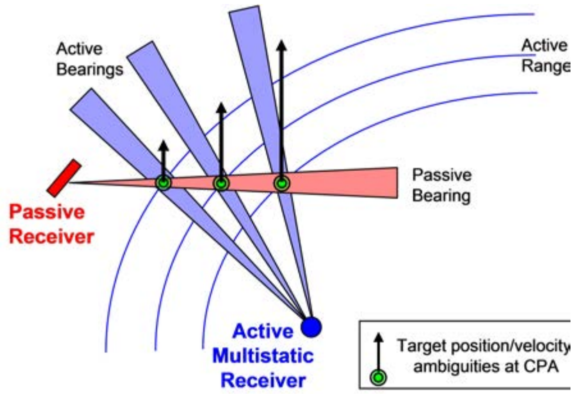

Fig. 1. Passive and active measurement fusion in a common Cartesian coordinate frame.

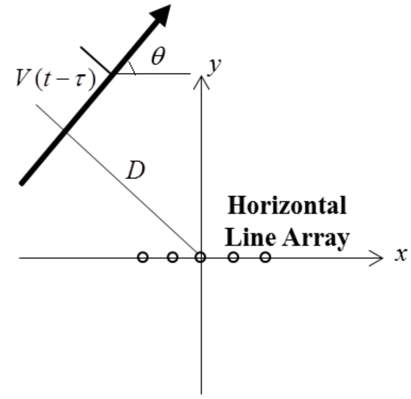

Fig. 2. Parameters that define a constant velocity trajectory.

will be perpendicular to the bearing line, for any assumed target range. Its speed will depend on the assumed CPA target range, as depicted in Fig. 1. Shorter range implies slower speed whereas longer range implies faster speed. Such passive information is ambiguous and therefore does not provide a complete estimate of the target's kinematic state.

Detections from an active sonar system readily provide precise estimates of both bearing and range on a single ping via the bistatic mapping [4] . If Doppler-sensitive waveforms are used, the target range-rate may also be estimated. However, the major issue with active sonar systems is overloading due to high false alarm rates due to reverberation clutter. Given the relative strengths and weaknesses of passive and active sonar systems, there are advantages to a synergistic, complimentary, and parallel use of both sensing types within a surveillance operation.

This paper describes an algorithm for initiating multistatic active tracking with a passive detection cue. Section II describes the passive processing, including the CPA-detector and the passive cue generation. Section III describes the conversion of the passive cue into Cartesian coordinates via a Gaussian Mixture representation. Section IV describes the multistatic active tracker. Section V describes the results of the algorithm on a simulated passive-active data set. Section VI gives conclusions.

II. Passive Detection Cue Generation

This section provides a brief description of the generation of a cue from a passive track in preparation for handing off to the active multistatic tracking system. A minimal parametric representation for a passive track is presented and an optimization algorithm is used to obtain estimates of the parameters. The details of the optimization algorithm, track parameter initialization and the performance of the optimization are discussed in a companion paper [6].

A. Minimal Parametric Representation of a Passive Track

A track is a sequence of measurements that relate to the motion of a target. The motion of the target is represented by a set of track parameters which are estimated from the measurements. The measurements in the passive tracks described herein are assumed to be taken from a horizontal line array. Horizontal line arrays yield angular measurements measured with respect to the array axis. These measurements are referred to as cone bearings.

If a sound wave approaches a horizontal line array from a distance, the wavefront forms a line perpendicular to the direction of travel. This wavefront impinges on the array elements with a time delay between array elements proportional to the cosine of the angle between the direction of travel and the array axis [3]. The relationship between time delay and angle is used in the beamforming process that generates the measurements. Because of this, cosine of the cone bearing is considered to be the raw measurement for purposes of estimating track parameters.

Before estimating track parameters, it is essential that the passive acoustic track be uniquely represented by a minimum number of well-defined parameters. A minimum parametric representation of a target trajectory is shown in Fig. 2 for a target on a constant velocity trajectory. The minimal representation uses time of CPA, $\tau \in (-\infty, \infty)$, target heading, $\theta \in (-\pi, \pi]$, target speed, $V \in (0, \infty)$, and CPA distance, $D \in (-\infty, \infty)$. It can be shown that cone bearing depends on target speed and CPA distance only through the ratio, $\nu = V/D \in (-\infty, \infty)$.

There is a known ambiguity, called the left-right ambiguity, in representing tracks generated from horizontal line array measurements. For any target trajectory, there is a corresponding trajectory that is symmetric about the axis of the array. The two target trajectories are indistinguishable because they yield exactly the same measurements. One of those target trajectories passes clockwise with respect to the sensor array and the other counterclockwise. If the definition of parameters includes the constraint $\nu \in (0, \infty)$, the parameter set represents a target trajectory that passes clockwise with respect to the center of the sensor array. The parameter set that define the clockwise trajectory is arbitrarily chosen for parameter estimation to uniquely define the track parameters which are called the unique track parameters. The track

parameters that define the counterclockwise trajectory are called the ambiguous track parameters. The ambiguous track parameter representation is equally valid, but is calculated from the unique track parameters rather than estimated. Both unique and ambiguous track parameters are passed as cues to the multistatic active tracking system. With track parameters as defined, the cosine of the cone bearing, $Q(t)$, can be expressed as in [3]:

$$\cos Q(t) = \frac{\sin\theta + \nu(t-\tau)\cos\theta}{\sqrt{\alpha^2 + \nu^2(t-\tau)^2}}, \tag{1}$$

where

$$\alpha^2 = 1 + (h + D)^2, \tag{2}$$

and h is the difference in depths between the target and the sensor array. For estimation purposes, $\alpha \approx 1$ is assumed [5].

A multi-dimensional non-linear optimization routine is used for estimating track parameters by minimizing the square error between the measurements and the measurement estimates based on the track parameters in a least squares approach [6].

B. Conversion to Normalized Coordinates

The passive track parameters must be converted from the 3-dimensional (3-D) space (τ, θ, ν) to 4-D Cartesian space $(x, y, \dot{x}, \dot{y})$ to initiate a track in the active tracker, where $\dot{x}$ and $\dot{y}$ represent target velocities in x and y directions. In the active tracker, a CPA distance will be introduced into the passive track space as an unknown parameter. A convenient method of representing the passive track is in normalized coordinates, i.e., the target state vector, $X = [x, y, \dot{x}, \dot{y}]^T$, normalized by the CPA distance, D. Mathematically, the normalized coordinate state, $\tilde{X} = [\tilde{x}, \tilde{y}, \tilde{\dot{x}}, \tilde{\dot{y}}]^T$, can be expressed as:

$$\begin{aligned} \tilde{x}(t) &= \frac{x}{D} = -\sin\theta + \nu(t-\tau)\cos\theta, \\ \tilde{y}(t) &= \frac{y}{D} = \cos\theta + \nu(t-\tau)\sin\theta, \\ \tilde{\dot{x}}(t) &= \frac{\dot{x}}{D} = \nu\cos\theta, \\ \tilde{\dot{y}}(t) &= \frac{\dot{y}}{D} = \nu\sin\theta. \end{aligned} \tag{3}$$

The normalized coordinate solution is given in array-centered coordinates. The equally valid ambiguous solution is also passed to the active tracker. The ambiguous state vector, $\tilde{X}_a = [\tilde{x}_a, \tilde{y}_a, \tilde{\dot{x}}_a, \tilde{\dot{y}}_a]^T$, is given by:

$$\begin{aligned} \tilde{x}_a(t) &= \tilde{x}(t) = -\sin\theta + \nu(t-\tau)\cos\theta, \\ \tilde{y}_a(t) &= -\tilde{y}(t) = -\cos\theta - \nu(t-\tau)\sin\theta, \\ \tilde{\dot{x}}_a(t) &= \tilde{\dot{x}}(t) = \nu\cos\theta, \\ \tilde{\dot{y}}_a(t) &= -\tilde{\dot{y}}(t) = -\nu\sin\theta. \end{aligned} \tag{4}$$

Covariance matrices for both the target and ambiguous state vectors are also calculated using a Monte Carlo method and passed to the active tracker [6]. Measurements of the cosine of the cone bearings arrive sequentially. After each measurement, there is a need to evaluate the quality of the passive track parameter estimates. If the parameter estimates are sufficiently accurate (i.e. if the track quality measure exceeds a threshold), a passive cue is sent to initiate the active tracker.

III. Gaussian Mixture Representation of a Passive Cue

Due to uncertainty in passive track generation, the target is assumed to be located at any range between the minimum and the maximum detection ranges, with a corresponding speed depending on the assumed range. In addition, the passive track information must be represented in Cartesian coordinates in order to be fused with an active tracker where the target states and measurements are typically represented in Cartesian space. A coordinate conversion method from passive bearing measurements to Cartesian coordinates is given in [7]. In that approach, a bivariate normal distribution models the 2-D (x and y positional coordinates) target state, assuming a uniform joint distribution in range and bearing from the receiver.

In our approach, we represent the target state distribution in 4-D Cartesian coordinates (x and y positional and velocity coordinates) by a sum of 4-D Gaussian components (also referred to as Gaussian Mixture (GM)). With a single component Gaussian representation, a conventional centralized Kalman-Filter based active tracker, which performs explicit data associations, may be sensitive to high false alarm density. The single Gaussian representation may be initially associated with false contacts and may fail to associate target-originated detections in future ping times. In that case, a false track may be initiated. With multiple components covering the target state distribution over a sequence of ping times, target-originated detections are maintained in addition to false contacts. Over a sequence of ping times, a kinematically consistent track will emerge among the set of multiple tentative tracks and may be confirmed as a highly probable target track. In addition, the inclusion of velocity hypotheses allows for effective and immediate fusion with active scans that include Doppler measurements.

We assume the CPA distance, D, as a random variable uniformly distributed between $D^{\min}$ and $D^{\max}$ (i.e., $p(D) = U(D^{\min}, D^{\max})$, where p represents a probability density function, U represents the uniform density function and $D^{\min}$ and $D^{\max}$ represent the expected minimum and maximum CPA detection ranges of the passive system. We express D by means of a GM representation as in [8]:

$$p_A(D; n) = \sum_{i=1}^{n} \alpha_i \mathcal{N}(D; r_i, \sigma_i^2), \tag{5}$$

$$\sum_{i=1}^{n} \alpha_i = 1, \tag{6}$$

where p_A represents a GM density function, n is the number of Gaussian components, α_i is the weighting factor of component i and $\mathcal{N}(D; r_i, \sigma_i^2)$ is a normal density function of D with mean r_i and variance σ_i^2 for component i.

We set the weighting factors of all the components to be equal ($\alpha_i = \alpha = 1/n$) and the variances of all the components to be equal ($\sigma_i^2 = \sigma^2$). Mean values r_i are equally spaced in the interval $[D^{\min}, D^{\max}]$ (i.e., $r_i = D^{\min} + (2i-1)(D^{\max} - D^{\min})/2n$). The values of n and σ are determined to minimize the error in the approximation $U - p_A$ in some prescribed sense.

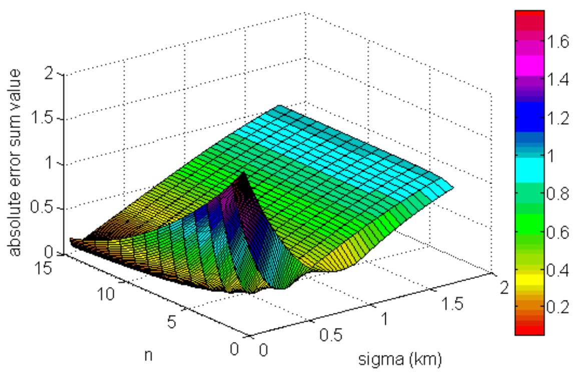

Fig. 3. Objective function values vs. σ and n for $U(500\text{ m}, 3000\text{ m})$.

We solve the following optimization problem: find the minimum number of Gaussian components, n^*, and the optimal standard deviation, $\sigma^*(n^*)$, that is smaller than or equal to a prescribed error tolerance in the approximation $U - p_A$. This optimization problem is solved in two stages. The first stage involves choosing n and the second stage involves solving $\sigma^*(n)$ for a given n. The two stages are repeated until n^* and $\sigma^*(n^*)$ are found.

This procedure can be summarized as follows. For a given n, $\sigma^*(n)$ is chosen to minimize the following optimization objective function:

$$\int_{-\infty}^{\infty} |U(D^{\min}, D^{\max}) - p_A(D; n)| dD. \tag{7}$$

As an example, the optimization objective function with respect to σ and n for $U(500\text{ m}, 3000\text{ m})$ is shown in Fig. 3. Observe that for a given n, the objective function with respect to σ is unimodal. For a fixed n, the resulting optimization is a one-dimensional non-linear optimization and the steepest descent algorithm with Armijo's rule line search is used to find the optimal value $\sigma^*(n)$ [9]. Given that the minimum and maximum allowable numbers of components and a prescribed error tolerance are specified, we use a binary search algorithm to find the optimal number of components. At each iteration, the algorithm chooses a middle integer number between the current minimum and maximum allowable numbers, and solves the optimization problem which minimizes (7). If the resulting objective function value is better, the middle number becomes the new maximum allowable number. If the resulting objective function value is worse, the middle number becomes the new minimum allowable number. The algorithm repeats until a pair of n and $\sigma(n)$ which is smaller than or equal to the error threshold is found and the the minimum, middle and maximum numbers are consecutive.

We then rescale the target state in normalized coordinates by multiplying with each Gaussian component which represents a CPA distance hypothesis in order to obtain a target state hypothesis in Cartesian coordinates with reference to the passive receiver state. Let D_i denote the i-th Gaussian component in $p_A(D)$, whose expected value and variance are given by r_i and σ_i^2. Let the expected value and covariance of normalized coordinate target state $\tilde{X}$ be denoted by $\hat{\tilde{X}}$ and Σ. Assuming D_i and $\tilde{X}$ are independent, the expected value and covariance of a target state hypothesis in the array-centered Cartesian coordinates, X_i, are obtained as:

$$E[X_i] = E[D_i\tilde{X}] = r_i\hat{\tilde{X}}, \tag{8}$$

$$\begin{aligned} Cov[X_i] &= E[X_iX_i^T] - E[X_i](E[X_i])^T \\ &= E[D_i^2\tilde{X}\tilde{X}^T] - r_i^2\hat{\tilde{X}}\hat{\tilde{X}}^T \\ &= (r_i^2 + \sigma_i^2)(\hat{\tilde{X}}\hat{\tilde{X}}^T + \Sigma) - r_i^2\hat{\tilde{X}}\hat{\tilde{X}}^T \\ &= r_i^2\Sigma + \sigma_i^2\hat{\tilde{X}}\hat{\tilde{X}}^T + \sigma_i^2\Sigma. \end{aligned} \tag{9}$$

The array-centered Cartesian coordinates are then translated into a common Cartesian coordinate frame.

IV. Active Multistatic Target Tracking

Each passive detection cue is decomposed into $2n$ target state hypotheses (n hypotheses for a unique solution and n hypotheses for an ambiguous solution) in 4-D Cartesian coordinates. All target state hypotheses are fed to the active multistatic target tracker to initiate active multistatic tracking. In this section, we provide a description of active target tracking and hypothesis selection from a set of $2n$ hypotheses.

A. Kalman-Filter Multistatic Target Tracking

Multistatic processing provides the following measurements which relate to target kinematics: bistatic time-of-arrival, bearing, and bistatic range-rate if Doppler-sensitive waveforms are used. The multistatic tracker used in the pQa algorithm is based largely on the description found in [10].

Time-of-arrival, bearing, and source/receiver positions are used to calculate converted, debiased x-y geographic positions of the detections and their uncertainties using non-linear bistatic transformations [11]. An Extended Kalman Filter (EKF) is implemented which assumes converted positional measurements and non-linear, bistatic range-rate measurements.

When the multistatic tracker is operating without cooperative passive sensors, simple logic-based track confirmation (M out of N scans with associated detection contacts) and termination (K consecutive misses) schemes are used. However, when used in conjunction with passive sensors, only the passive cue is used to initiate tentative active tracks. Each passive cue initiates a set of $2n$ components or hypotheses of tentative active tracks; one track for each hypothesis of the cue's GM representation. The calculation of the track score initiated with each component and the track confirmation and termination schemes are discussed in the next subsection.

Contacts from each active scan are considered for association to existing tentative or confirmed tracks if they reside within an association gate and have signal-to-noise ratio (SNR) amplitude level above the tracker's input threshold. A nearest

neighbor data association scheme is implemented. Longer, confirmed tracks get priority over shorter, tentative tracks, for contact associations. Target motion is modeled using a 2-D nearly constant velocity motion model.

B. Track Scoring and Hypothesis Selection

The tracking algorithm is initiated by a passive cue with multiple tentative tracks. Since at most one track can be originated from one passive cue, we compute a track score to describe how likely or unlikely it is that each track hypothesis originates from detections of the true target by considering kinematic and signal-related contributions.

The track score is defined as the log of the likelihood ratio (LLR) of the hypothesis that the set of observations in the track are from the same target and the hypothesis that the track is a collection of false alarms. The score is initially set to zero at the time of the first observation corresponding to an unknown state. Thereafter, upon the receipt of data on scan m, the score for track n is updated according to the relationship [12]:

$$L_n(m) = L_n(m-1) + \Delta L(m), \qquad (10)$$

where

$$\Delta L(m) = \begin{cases} \ln(1-\text{PD}) & \text{no track update on scan } m, \\ \Delta L_U & \text{track update on scan } m, \end{cases}$$

$$\Delta L_U = \ln\left\{\frac{\text{PD}\cdot V_C}{2\pi\text{Pfa}\sqrt{|S|}}\right\} - \frac{d^2}{2},$$

PD = estimated probability of detection,
Pfa = estimated probability of false alarm,
V_C = volume of the measurement validation region,
S = innovation covariance matrix,
d^2 = normalized statistical distance function.

The track score for each hypothesized track is updated recursively using Eq. (10) for all the scans at each ping time. We use the Sequential Probability Ratio Test (SPRT) to confirm and terminate tracks. We calculate the track confirmation and deletion thresholds T_1 and T_2:

$$T_1 = \log\left(\frac{\beta}{1-\alpha}\right), \quad T_2 = \log\left(\frac{1-\beta}{\alpha}\right), \qquad (11)$$

where α and β represent false track confirmation probability (type I error) and true track deletion probability (type II error). If the updated track score for a hypothesized track is less than T_1, the track is deleted. If the score is greater than T_2, the track hypothesis is selected and the rest of the track hypotheses associated with the cue are deleted. If the score is between T_1 and T_2, the tracker continues tracking all the remaining hypotheses.

V. Algorithm Results on Simulated Data

To provide a test dataset with sufficient fidelity, including acoustic effects, the Passive-Active Contact Simulator (PACsim) simulation tool has been developed [13]. This simulator produces sonar target detection or contact information consisting of SNR, bearing, time-of-arrival (if active), and Doppler (if active). Measurement errors and signal fluctuations are also modeled. Contacts corresponding to false passive targets (surface ships) and active targets (bottom clutter) may be generated and inserted into the dataset. Finally, active reverberation clutter is simulated in each ping's data by creating active contacts which are randomly distributed in receivers' measurement spaces and in SNR amplitudes.

Fig. 4 shows the PACsim-generated scenario used in the pQa algorithm evaluation. Three passive, fixed, bottomed receivers are shown to the west (black). The passive receivers are oriented along the x-axis. Two active sources (squares) are positioned amongst a field of 11 active multistatic receivers (red). The passive receivers are modeled as fixed horizontal line arrays; the active receivers are assumed to be planar arrays. Ping transmissions are made once a minute, alternating between the two sources and between FM/CW waveforms. The true target of interest is shown initially moving eastward at about 5 knots. It first passes by the passive receivers, between passive receivers 1 and 2, and then proceeds to pass through the active multistatic field with two maneuvers. In this example, there is no false passive target but there is a single fixed false active target. The scenario is of duration 8.8 hour. Typical values for passive and active sonar signal processing are assumed.

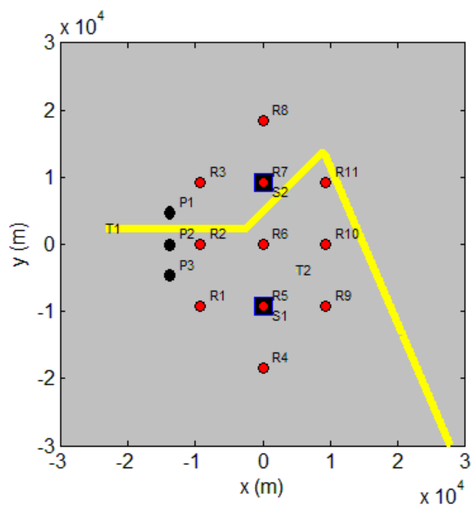

Fig. 4. PACsim scenario showing passive receivers (black), sources (squares), active receivers (red), true target trajectory (yellow), and a false fixed target (T2).

Using PACsim, processed, passive measurements of target bearing and SNR for each of five assumed characteristic target frequencies are simulated for each of the passive receivers over time. Doppler shifts are not modeled in the simulation, and therefore the pQa algorithm does not yet exploit this information. With such a simulation, frequency line-tracking is not required as a pre-process to the pQa algorithm. Future simulations will more realistically simulate this passive Doppler information and a frequency line-tracker will be implemented;

here we assume the frequency line-tracking has successful been done. The next step is a frequency grouping process, which combines frequencies that share common bearing-time trajectories. Passive detection is declared for times when p out of q of the target's characteristic frequencies have positive signal excess. In this example there are 5 characteristic target frequencies and the parameters for p of q are 3 of 5.

Fig. 5 shows an example of simulated noisy cone bearing measurements over time. The CPA detector and passive cue generation algorithm of Section II is used and an initial cue estimate is obtained at time 3700 s. A passive cue of sufficient quality is obtained and reported at time 4020 s for the CPA event yet to occur at 4500 s on the simulated data. The process computes the cue's normalized Cartesian target state estimates (position and velocity for both sides of the line array) and associated error covariances. These are then provided to the Gaussian mixture target hypothesis generation module of Section III.

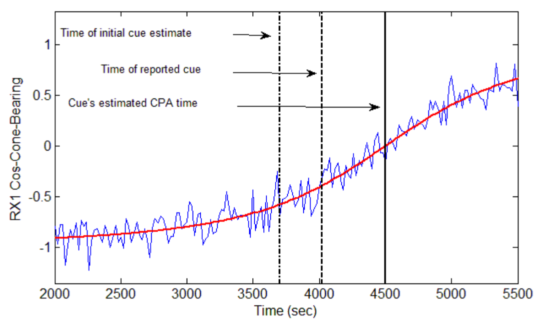

Fig. 5. Cosine of cone bearing measurements over time.

A set of target state hypotheses over a range interval of 500 m to 3000 m on each side of the reporting array is computed. The Gaussian mixture representation of uniform distribution in the specified interval is shown in Fig. 6. For an error tolerance of 0.1, the resulting GM representation includes 7 components, each with a σ of 160m. For passive receiver 1 (P1), it produces 14 components, 7 on each side of the array for the time of its reported passive cue. These components correspond to active tentative track initiation hypotheses. The hypotheses for positions and 3-σ error ellipses corresponding to the cue at P1 are shown in Fig. 7. The true location of the target at that time is shown by the green dot (nearest to component 12). The target reaches CPA when it passes directly south of the array, as shown by the yellow dot. Other passive receivers may detect CPA events also, but here we focus our analysis on the cue produced by P1.

Fig. 8 shows the target velocities (in x and y directions) for the set of hypotheses. They show eastward headings over 0.5–2.5 m/s, a range which encompasses the true velocity shown (by the green dot) at around 2 m/s (or 5 knots). The corresponding 3-σ error ellipses are also shown. We see that the hypotheses which are further from the array have increased target speed as expected.

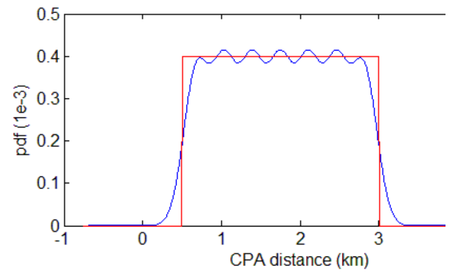

Fig. 6. Gaussian Mixture representation of the uniform density function of the CPA distance over $[500\text{ m}, 3000\text{ m}]$ with an error tolerance of 0.1.

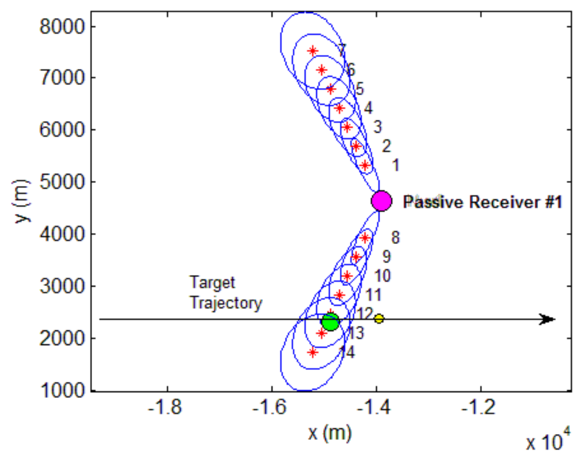

Fig. 7. Decomposition of passive receiver 1's (magenta) cue into a set of hypothesized positions via Gaussian mixture representation, to be used in active track initiation. Mean values are shown in red stars and 3-σ error ellipses are shown in blue. The target's true position at the time of the reported passive cue (green dot) and at the time of CPA (yellow dot) are shown.

From the time of the reported cue, active multistatic sonar scans are simulated using PACsim. Each scan includes multiple detection contacts for a source-receiver-waveform combination. In this case there were 11 scans per ping (one per receiver for a given source). A target contact is contained in the scan if the active sonar model indicated positive signal excess; otherwise no target contact is produced. There are 15 false alarms per scan on average which are distributed over the large surveillance area.

The passive cue's 14 hypotheses are used to initiate a set of tentative active tracks, each of which are updated with active contacts (true or false) that associate. If no contacts associate, the track "coasts". The LLR score for each hypothesis is updated after each scan. Fig. 9 shows the LLR scores for the 14 tentative active tracks generated by the passive cue of P1. The first active scan after the passive cue is scan number 737, where we see the LLR scores all starting at zero. Tentative track confirmation and deletion thresholds are established based on a PD of 0.1, Pfa of 0.05, false track

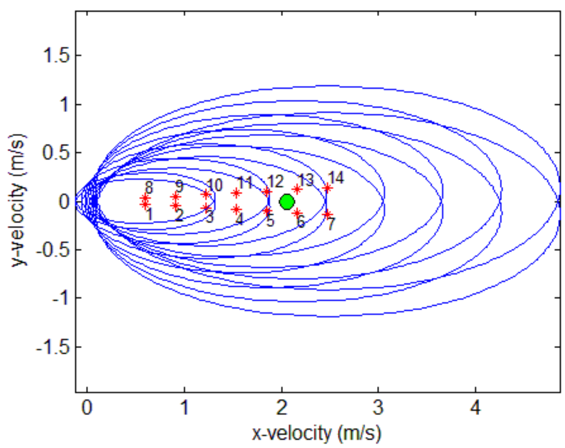

Fig. 8. The hypothesized velocities corresponding to the positional hypotheses of Fig. 7. Mean values are shown in red stars, 3-σ error ellipses are shown in blue and the true target velocity is shown in the green dot.

confirmation probability, α, of 0.001, and true track deletion probability, β, of 0.01. The blue curve corresponds to the winning hypothesis (hypothesis 12) which ultimately rises above the threshold and confirms an active track. The other curves (many of which overlay one another) represent the other 13 hypotheses and decline steadily until they are deleted (at around scan 780) and removed from consideration. Sections of the curve with slight or large negative slope correspond to track coasts or false alarm associations, respectively. Positive slopes indicate when true target contact associations are made. The time duration corresponding to this track confirmation in this case is about 15 minutes.

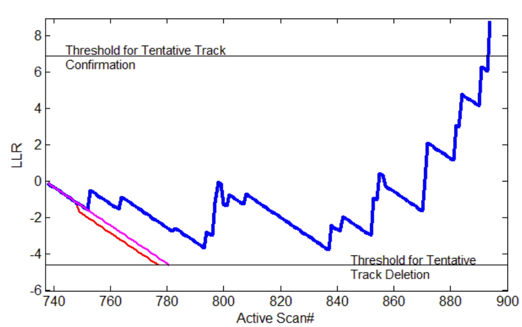

Fig. 9. The active tracking LLR scores for each of the 14 hypotheses of the passive cue. The winning hypothesis is shown in blue; the other hypotheses follow the magenta and red curves.

Once the track hypothesis is confirmed, active tracking continues until the track termination criterion is satisfied. The active tracking output is shown in Fig. 10, for the entire scenario duration. There is a single, continuous, high quality output track, shown in blue. We see that it starts near the point of passive detection and follows the target trajectory until it gets into an area where detection capability drops. The passive cue has effectively initiated active tracking and made a successful detection handoff between heterogeneous sensing systems.

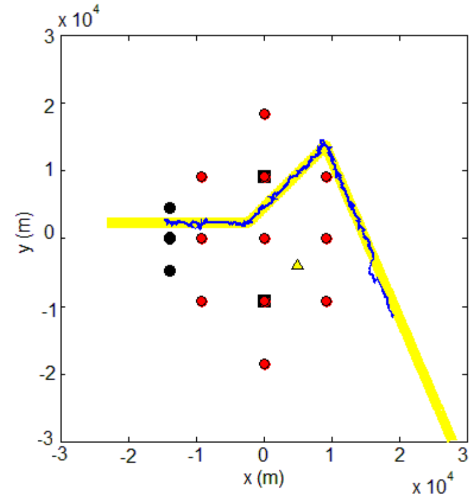

Fig. 10. Multistatic active tracker output with the use of the passive cue to focus target search and initiate active tracking. Passive receivers (black); active receivers (red circles); active sources (black squares); target true trajectory (yellow); output active tracks (blue).

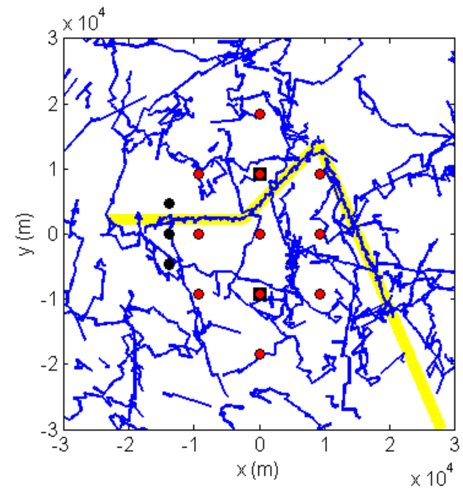

Fig. 11. Multistatic active tracker output without the use of a passive cue to focus target search results in many false tracks. Passive receivers (black); active receivers (red circles); active sources (black squares); target true trajectory (yellow); output active tracks (blue).

The false alarm reduction potential of this algorithm is now demonstrated. Fig. 11 shows the result of active multistatic tracking on the same dataset, but without utilizing passive sensors, detections, or cues. Here we used a track M/N initiation criteria of 5/55. Since every active detection contact is used to initiate a tentative track, and many of the tentative tracks become confirmed, there are 124 total tracks generated. The active multistatic system, operating alone, does not have a cue to help focus the search and limit the number of

erroneous false tracks that are produced. Tracking on the target is observed to be about the same as was achieved with the passive cue initiation; however there are two points along its trajectory where undesirable fragmentation events occur.

VI. Conclusion

The pQa algorithm has been described, which includes CPA detection, conversion into a set of Cartesian track-initiation hypotheses, and active multistatic tracking. The algorithm shows an effective way to fuse the available information from passive line arrays and active multistatic systems. The passive cue is effective in allowing the active multistatic system to localize and continue track-holding on the target. The benefit of this cueing approach in reducing false track rate has been demonstrated.

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